The Effect of Social Groups and Gender on Pedestrian Behaviour Immediately in Front of Bottlenecks

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Abstract: Pedestrian crowds are unlikely to be composed of identical individuals. To understand how pedestrians interact, it is important to investigate what effect differences between individuals have on the observed movement dynamics. Two key aspects that can distinguish individuals are their gender and their membership in small social groups, such as families or groups of friends. Here, I report findings from a controlled experiment in which a pedestrian crowd has to pass a narrow bottleneck. In one experimental treatment, participants are asked to move independently from others and in the other treatment, they are asked to move in groups of four individuals. Trajectories of individuals, as well as group membership and gender are recorded. Investigating egress times produces conflicting results across two separate crowds in different experimental locations and I therefore investigate microscopic pedestrian behaviour. I present statistical models that capture how pedestrian behaviour immediately in front of the bottleneck affects the time gap between consecutive pedestrians passing through the bottleneck. This provides a rigorous approach to test whether individuals from the same social group or gender interact differently to individuals from different groups or genders. My analysis suggests that being from the same or from different social groups does not have an effect on time intervals between pedestrians. This suggests that in my data, group membership does on average not affect behaviour immediately in front of the bottleneck. Interestingly, my analysis suggests a gender effect: men follow women more closely than vice versa. Possible explanations for this range from the way mixed-gender couples move to physical differences between genders. These findings demonstrate the potential of my approach to uncover detailed aspects of interactions underlying pedestrian behaviour.

Keywords: pedestrian dynamics; collective behaviour; social interactions; social groups; gender effects; statistical modelling

1 Introduction

In pedestrian crowds, the overall crowd movement results from interactions between individuals, making this an example of collective behaviour [1]. The social interactions between pedestrians have been investigated widely with the aim to gain an understanding of crowd dynamics that could ultimately inform building design and event planning, for example [2]. While some research has assumed for simplicity that all individuals are identical and behave and interact in the same way, other research suggests that this view may be too simplistic (e.g. [3-5]). Here, I focus on how two important aspects, that distinguish individuals, affect social interactions between pedestrians: individual's gender and their membership in small social groups composed of friends or families.

Previous work has investigated gender-specific differences in the speed distributions of pedestrians [3] or in the risk-taking behaviour of pedestrians when crossing roads [6], for example. The effect of social groups on pedestrian movement in crowds has similarly been studied from different angles, including the evaluation of reports by survivors of emergencies [4-5], [7], observational studies to establish everyday behaviour in social pedestrian groups [8-9] and efforts to develop computer simulation models that capture the salient aspects of social group movement within crowds [10-13]. In this contribution, I focus on how gender and social group membership affect social interactions in situations when a crowd moves in one direction and has to pass a narrow bottleneck, such as an exit door. Crowd dynamics at bottlenecks are directly relevant for building design or event planning and because of its ubiquity in the literature, this scenario can also be viewed as a benchmark for research into pedestrian behaviour.

To the best of my knowledge, effects of gender on social interactions between pedestrians at bottlenecks have been subject to little or no scientific investigation. In some societies, traditional (and outdated) etiquette demands that men hold doors open for women [14]. However, it is difficult to see how this could generalise to crowded situations, especially if no doors need to be opened. To pre-empt criticism, it should also be noted that when exploring gender effects, it can be difficult to establish the exact causes of observed effects. For example, average differences in physiology could explain differences in speed between genders instead of intrinsic behavioural differences.

A number of experimental and theoretical studies have investigated how the presence of social groups affects the unidirectional flow or egress through a bottleneck. Based on observations of pedestrian behaviour during emergencies (e.g. [4]), simulation models typically assume that individuals in social groups attempt to stay in close proximity to each other, which can lead to increased simulated egress times compared to independently moving pedestrians [10],[12]. The experimental evidence to date is limited and ambiguous. Some results suggest increased egress times when social groups are present [12], others predict a reduction in egress times [15] and another study (albeit with small crowd sizes) suggests social groups have an effect on egress times, but not immediately at bottlenecks [16]. Based on this brief survey of the literature, I suggest that further work is needed.

In the following, I present data from a controlled experiment that was designed to test the effect of social groups on egress times at bottlenecks. To obtain robust results from a limited number of replicate experiments (a common problem in pedestrian research), I extend a previously developed statistical modelling framework [17] to investigate the effect of social group membership and gender on interactions immediately in front of bottlenecks.

2 Methods

2.1 Experiments

I conducted identical experiments at two separate locations with one group of volunteers at each location. The first group was composed of 71 visitors of the DANA centre at the Science Museum in London and the second consisted of 39 students at the University of Bristol. In the experiment, participants were asked to walk through a narrow bottleneck at the end of a corridor. A still image of the experimental setup is shown in Figure 1. I filmed experiments with a camera positioned directly above the 0.6 m wide and 1.5 m long bottleneck. The corridor in front of the bottleneck was 2 m wide and at the start of experiments participants were lined up 3 m away from the bottleneck. All barriers were marked using chairs or tables. I manually recorded the head positions of pedestrians in each frame of my video recordings (in pixels) at a rate of 10 and 15 frames per second for the London and Bristol data, respectively. By focussing my analysis on pedestrian positions in close proximity to the bottleneck, I reduced errors in pedestrian trajectories caused by camera distortion. In previous work [17], a first analysis of this data is presented, which I extend here.

I tested two experimental treatments with each group of participants. I designed the experimental treatments to simulate situations when pedestrians move independently and when they move in small social groups. In the individual treatment, I gave participants the following instructions: 'imagine you are commuters at rush hour. Don't wait for others when exiting.' In the social treatment, I assigned participants to groups of 3-4 individuals (indicated by numbered hats, e.g. all group members wear hats with the number 3). I instructed participants as follows: 'stay in your group. Try to exit together. Behave as you would if you were a group of friends.' Many of the participants arrived in social groups and this social attachment was used wherever possible in the construction of social groups for the experiment. However, I did not record data on social affiliations. In London, this resulted in seventeen groups of 4 and one group of 3 individuals and in Bristol, I obtained nine groups of 4 and one group of 3 individuals. In all trials, I instructed participants to walk at a normal speed and to avoid physical contact.

In the London experiment, I first conducted two runs under the social treatment and then two runs under the individual treatment. In the Bristol experiment, I reversed the order in which I tested the experimental treatments.

To investigate the effect of social group membership on microscopic interactions between pedestrians, I identified the hat number corresponding to each of the trajectories recorded. Similarly, to explore any effects gender had on interactions in front of bottlenecks, I categorised the gender of pedestrians to male or female, based on their clothes, hair and body shape in video recordings, and recorded this information alongside the corresponding trajectories. While it could be argued that my categorisation is subjective and somewhat limited, I suggest that in the interest of parsimony and given the data collected, this is the most suitable approach. I expect discrepancies between my gender assignment and the biological sex of participants to be infrequent.

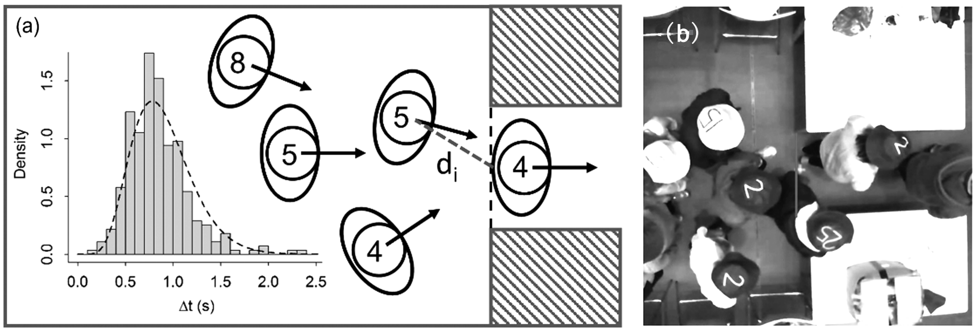


Fig. 1 (a) Schematic illustration of the experiment and data used in statistical models. Models predict the time interval between consecutive pedestrians, Δt, based on the distance of the closest pedestrian to the exit (d_i), as well as gender and social group membership (indicated by hat numbers, e.g. 4, 5, 8). For example, a change in hat number between consecutive pedestrians could affect the length of the time interval between them. The inset shows the distribution of time lapses, Δt, for the London data with a Gamma distribution fit. (b) Still image of the experiment in Bristol. Hat numbers are clearly visible. The faint vertied line in front of the bottleneck indicates the exit location used in the analysis

2.2 Statistical Models

To quantify the effect social group membership and gender have on microscopic interactions in front the bottleneck, I extend a previously developed framework of statistical models [17]. In these models, I assume that the time lapse between two consecutive pedestrians passing through the bottleneck, Δt_p (p indicates the temporal ordering of time lapses), depends on the positions, gender and group membership of pedestrians in front of the bottleneck. The distribution of time lapses provides useful measures. Its mean is related to the pedestrian flow through the bottleneck and the frequency of large outlier values indicates the likelihood of jams in which the pedestrian flow stops temporarily.

Specifically, I model the time lapse random variable T_p which takes values Δt_p using a gamma distribution, $T_p \sim \Gamma(\mu_{p\text{-}1}, \sigma)$, with mean $\mu_{p\text{-}1}$ and variance σ. I treat σ as a constant model parameter. As I consider a narrow bottleneck, only one pedestrian at a time can enter it. In our previous analysis [17], we investigated different models for $\mu_{p\text{-}1}$ based on the relative positions of pedestrians in front of the bottleneck at the time point when the previous pedestrians passed through the bottleneck (as indicated by the index p-1). We found that a model based on the distance of the nearest pedestrian to the exit, d_i, was best supported by both of our datasets. Now I use this model as a starting point and extend it to test for gender and group membership effects. The model for $\mu_{p\text{-}1}$ therefore takes the following form:

$$\mu_{p-1} = (\alpha_1 d_i - \alpha_2)^2 + e^{S_{p-1}} \quad (1)$$

In equation 1, α_1 and α_2 are model parameters, d_i is the distance of the pedestrian nearest to the exit at the time point when the previous pedestrian has entered the bottleneck (see figure 1 for an illustration) and the quantity $S_{p\text{-}1}$ contains several explanatory factors that are designed to capture gender and group membership effects. I use the exponential of $S_{p\text{-}1}$ in my model formulation to ensure that explanatory factors which may increase or decrease $\mu_{p\text{-}1}$ can be combined easily whilst ensuring that $\mu_{p\text{-}1}$ remains positive. I consider four explanatory factors, w_1, w_2, w_3 and w_4 that are combined linearly in $S_{p\text{-}1}$, such that $S_{p\text{-}1} = \alpha_3 + w_1 + w_2 + w_3 + w_4$, where α_3 is a model parameter.

The first explanatory factor captures a general treatment effect or, equivalently, an effect of the order in which treatments are tested (recall that the order in which the treatments were tested differed between the London and Bristol experiments). I set $w_1 = \alpha_4 X_{p\text{-}1}$, where α_4 denotes a model parameter and $X_{p\text{-}1}$ takes value zero if the data point is recorded in the individual treatment and value one if it is recorded in the social treatment. If α_4 takes positive values, this indicates that time lapses, Δt_p, in the social treatment are generally longer. For the London experiment this would suggest that the time lapses in the first set of two runs are longer and for the Bristol experiment it would suggest that time lapses are longer in the last two runs.

The second explanatory factor tests if there is a difference in the time lapse between members of the same social group compared to individuals from different social groups. Similar to above, I set $w_2 = \alpha_5 Y_{p\text{-}1}$, where α_5 denotes a model parameter and $Y_{p\text{-}1}$ takes value zero if there is no change in hat number between consecutive pedestrians in the social treatment and value one if there is a change in hat number or if the data is recorded in the individual treatment. Therefore, if α_5 takes positive values, this indicates that time lapses are larger between independent individuals.

With the third explanatory factor, I test if there is an effect on the time lapse between consecutive pedestrians when pedestrians of the same or different genders follow each other. One reason for including this explanatory factor is that there may be a difference in how closely pedestrians of different genders want to follow each other compared to pedestrians of the same gender. I model such effects by $w_3 = \alpha_6 U_{p\text{-}1} + \alpha_7 V_{p\text{-}1}$, where α_6 and α_7 denote model parameters. The dummy variable $U_{p\text{-}1}$ takes value one when a male pedestrian enters the bottleneck after a female pedestrian. $V_{p\text{-}1}$ takes value one when a female follows after a male pedestrian. For all other scenarios including when there is no difference in gender between consecutive pedestrians, the dummy variables take value zero. To give an example, if α_6 takes positive values, this indicates that time lapses are larger when a male follows after a female pedestrian compared to the base line when there is no difference in gender.

The final explanatory factor tests for the effect different combinations of genders in front of the bottleneck have on the observed time lapse. I consider the two pedestrians closest to the exit and set $w_4 = \alpha_8 Q_{p\text{-}1} + \alpha_9 Z_{p\text{-}1}$, where α_8 and α_9 are model parameters. $Q_{p\text{-}1}$ takes value one if the two closest pedestrians are both male and zero otherwise. Similarly, $Z_{p\text{-}1}$ takes value one when the two closest pedestrians are both female and zero otherwise. The rationale for including the explanatory factor is that cultural norms may cause pedestrians of one gender to always let the pedestrians of the other gender exit first, even if this causes a time delay (e.g. traditionally, men used to hold doors open for women in some societies [14]).

I investigated additional explanatory factors, such as a general gender effect or effects of differences in hat number between the two pedestrians closest to the bottleneck. However, their values were correlated with other explanatory factors and I therefore did not include them in the final model.

2.3 Statistical Analysis

I use a standard maximum likelihood approach to fit the full statistical model to my two datasets [18]. Details of this procedure specific to my modelling framework can be found in previous work [17]. I use residual plots to ensure that model assumptions hold (not shown for conciseness). When fitting my model, I only consider data when at least two pedestrians are still in front of the bottleneck. This results in 276 data points for the London experiment (4 runs with 71 participants) and 147 data points for the Bristol experiment (4 runs with 39 participants; in one run, I only record the exit time, but not the trajectory of the last pedestrian).

Model fits yield maximum likelihood estimates for the model parameters. I obtained standard errors for parameter estimates using 1000 bootstrap samples of the data. For each bootstrap sample, I constructed a dataset of the same size as the observed data by sampling from the observed data with replacement. I then fit the full model to this resampled dataset and recorded the parameter estimates. The standard deviation of the parameter estimate distribution obtained from 1000 such resampling procedures provides a standard error estimate [19].

I use likelihood ratio tests to test the hypothesis if including parameters significantly increases the likelihood of models [18]. Briefly, this test compares the maximum likelihood of the full model to a reduced model where the parameter(s) under investigation are set to zero. This test should not be interpreted in terms of effect sizes of explanatory factors. Rather, it provides evidence for whether model parameters should be set to zero (i.e. not included in the model).

3 Results and Discussion

First, I investigate if the experimental treatments had a global effect on the observed egress times in the experiments. Fig. 2 shows that in the London experiment, egress times were larger in the social treatment, while in the Bristol experiment this trend is reversed. As I changed the order in which I tested the treatments in the two experimental locations, I cannot rule out the possibility that effects of the social treatment are masked by stronger effects relating to the order in which experimental runs are conducted (e.g. participants might get used to the experimental setup and exit faster in later runs). To be able to make clear statements on the global effects of my treatments, a larger number of replicate experiments with different groups of participants is required. These results demonstrate the importance of including a sufficient number of independent replicates into experimental studies.

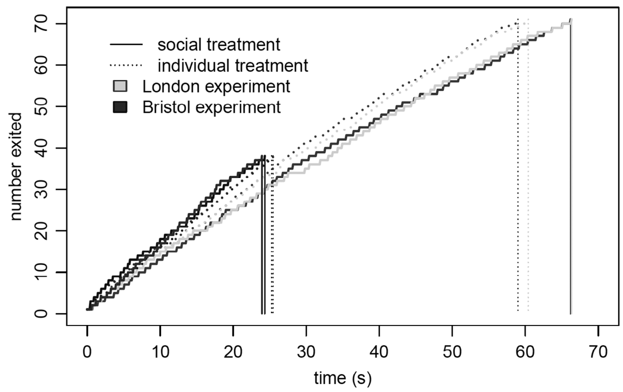


Fig. 2 Number of pedestrians who have exited plotted against time for the London and Bristol experiments. I plot data for each run of the experiment. Lighter/darker colours indicate later/earlier runs and dashed/solid lines indicate the individual/social treatments, respectively. Vertical lines indicate the total egress time

As the data is too limited for reliably establishing global effects, I investigate effects of the treatments, as well as gender, on interactions immediately in front of the bottleneck using my statistical model. I report the results from fitting the model to the experimental data in Table 1 and Table 2.

For the London experiment, I find that only the explanatory factor w_3, which captures effects of pedestrians of different genders following each other, has a small p-value (Table 1). All other p-values are high. This suggests that I do not have sufficient evidence to reject the hypothesis that the parameters associated with the explanatory factors w_1, w_2 and w_4 take the value zero (i.e. have no effect). This means that based on my analysis, social group membership (factors w_1 and w_2) does not help to explain the observed time lapses between consecutive pedestrians. In addition, I find high estimated standard errors for most parameter estimates. This indicates that the trends in the data that are associated with the different explanatory factors are not particularly robust. This could be an inherent feature of the data or a result of a relatively small data set. While the effect sizes of explanatory factors on time lapses are generally small (less than 0.1 s), the parameter estimates for w_3 suggest that male follow female pedestrians more closely and female follow male pedestrians less closely when compared to the baseline of pedestrians of the same gender following each other. I discuss this finding in more detail below.

Table 1 Model fitting results for the London experiment. I show results for the four explanatory factors related to group membership or gender effects. In the first column, I indicate in brackets the baseline against which the observed effects should be compared (see methods for details). I report the test statistic for the likelihood ratio test, indicating the degrees of freedom used in this test in brackets (equal to the number of free parameters for explanatory factor under consideration). P-values are from this test and I report effect sizes on time lapses for each parameter separately. Estimates for remaining model parameters: $\alpha_1 = 0.001 \pm 0.001$; $\alpha_2 = -0.592 \pm 0.180$; $\alpha_3 = -1.714 \pm 1.988$; $\sigma = 0.065 \pm 0.009$. All parameter estimates are from the full model. The letters 'm' and 'f' denote 'male' and 'female', respectively. By 'f→m', I denote that a male follows after a female pedestrian

Explanatory factor	Parameter estimate ± s.e.	Test statistic, D (d.f.)	p-value	Effect size against baseline (secs)
w_1, treatment effect (individual)	$\alpha_4 = 0.284 \pm 1.381$	2.219 (1)	0.136	0.059
w_2, change in hat number (no change)	$\alpha_5 = -0.009 \pm 1.113$	0.003 (1)	0.959	−0.002
w_3, change in gender (no change)	$\alpha_6 = 0.426 \pm 1.002$ [m→f], $\alpha_7 = -0.269 \pm 2.952$ [f→m]	9.963 (2)	0.007	0.096 [m→f], −0.043 [f→m]
w_4, gender of two closest (1m, 1f)	$\alpha_8 = 0.030 \pm 3.357$ [2m], $\alpha_9 = 0.018 \pm 0.484$ [2f]	0.041 (2)	0.980	−0.005 [2m], 0.003 [2f]

My findings for the Bristol experiment (Table 2) generally match the results for the London experiment with one important exception which I discuss in more detail below. As before, I find a low p-value for the explanatory factor w_3 and parameter estimates suggest the same effects (men follow women more closely and vice-versa when compared to the baseline of no difference in gender between consecutive pedestrians). Explanatory factors w_2 and w_4 both have nonsignificant p-values and they therefore do not help to explain the observed time lapses.

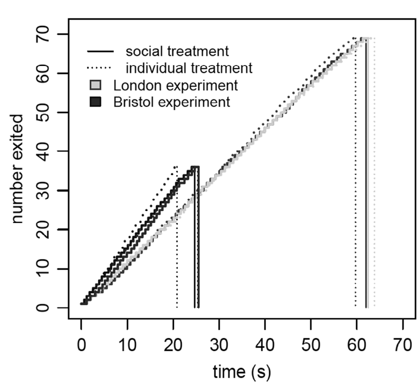
In my results for the Bristol experiment (Table 2), I additionally find a low p-value for the explanatory factor w_1. In contrast to the London experiment, I find a negative parameter estimate for α_4, the parameter in w_1. This could suggest that there is an overall reduction in the time lapses between consecutive pedestrians in the social treatment. However, as the order of the runs coincides with the treatments (the two runs under the social treatment are conducted last), I cannot reliably establish if this effect is due to the social treatment or the run order. In the London experiment, I first conduct two runs in the social treatment and then two runs in the individual treatment and I estimate α_4 to be positive, meaning that time lapses are higher in the first two runs. In the Bristol experiment, the order of the treatments was reversed and I estimate α_4 to be negative. Therefore, if I interpret w_1 as capturing a difference between the first set of two and the second set of two runs in both experiments, then the change in sign of α_4 between the London and Bristol experiments is consistent with a decrease in time lapses in the two later runs.

Table 2 Model fitting results for the Bristol experiment. See caption of table 1 for details. Estimates for remaining model parameters: $\alpha_1=0.003\pm0.001$; $\alpha_2=0.005\pm0.300$; $\alpha_3=-0.464\pm1.239$; $\sigma=0.052\pm0.006$. All parameter estimates are from the full model

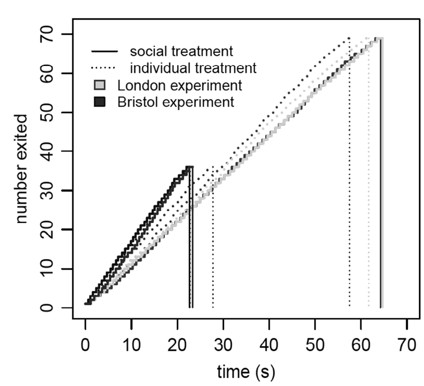
Explanatory factor	Parameter estimate ± s. e.	Test statistic, D (d. f.)	p-value	Effect size against baseline (secs)
w_1, treatment effect (individual)	$\alpha_4=-0.269\pm1.104$	12.575 (1)	0.0004	−0.148
w_2, change in hat number (no change)	$\alpha_5=-0.063\pm1.007$	0.338 (1)	0.561	−0.039
w_3, change in gender (no change)	$\alpha_6=0.181\pm0.230$ [m→f], $\alpha_7=-0.223\pm2.519$ [f→m]	12.813 (2)	0.002	0.125 [m→f], −0.126 [f→m]
w_4, gender of two closest (1m, 1f)	$\alpha_8=-0.013\pm0.677$ [2m], $\alpha_9=-0.001\pm0.272$ [2f]	0.017 (2)	0.991	−0.008 [2m], −0.001 [2f]

To reliably disentangle global treatment effects from consistent differences between earlier and later experimental runs, my model would have to be extended by accounting for both of these explanatory factors separately. I refrain from doing so here, because a full investigation of these factors should include experimental data where individual runs of different treatments are alternated-a scenario I did not test. However, seeing that any potential treatment effects appear to be masked by the order in which runs were conducted in my experiments and considering the generally low effect sizes I observed, I suggest that if there are any global treatment effects, they are likely to be weak.

To gain an insight into the extent to which my statistical model captures the global patterns I observe, I use the mean time lapses predicted by my model to obtain an estimate of the egress time for each experimental run (Fig. 3, compare to Fig. 2). First, I only include the explanatory factor w_3 into my model, as I found a low p-value for it in both data sets. This reduced model does not predict the separation between runs in the social and individual treatments I observe in the data (Fig. 3(a)). Second, I use the full model as reported in tables 1 and 2 to predict mean time lapses. For this model, I qualitatively obtain the same global pattern for the London data, but not for the Bristol data. This analysis suggests that while my statistical model successfully captures some factors that determine time lapses between consecutive pedestrians passing through a bottleneck, a substantial amount of variability in the observed dynamics remains unexplained.



(a)



(b)

Fig. 3 Number of pedestrians who have exited plotted against time for all experimental runs. Instead of plotting observed time lapses between consecutive pedestrians passing through the bottleneck, I plot the predicted mean time lapse, μ_{p-1}, from a statistical model fit to the data. (a) Predictions from a model in which all explanatory factors apart from w_3, which improves the model fit across both data sets, are removed from the model. (b) Predictions from the full model. Data is presented in the same way as in figure 2. Vertical lines indicate the total egress time

4 Conclusions and Outlook

In summary, I find that a social treatment effect on time lapses is likely to be weak if there is an effect at all. With regards to this finding, two important aspects should be considered. First, my experiment only simulates social groups and the behaviour of pedestrians outside of experiments may well be different. This issue could be addressed by applying my approach to observational data (e.g. similar to previous studies [8-9]). Second, pedestrian behaviour is likely to change considerably depending on the context. For example, in highly stressful evacuations, the effects of social groups may be different and possibly more pronounced than what I can observe in controlled experiments (e.g. see reports from crowd evacuations [4]).

Based on my findings reported here and in previous work [16], I suggest that in low-pressure egress situations, social groups within crowds can have an important effect on egress times, but that this effect is likely to be more substantial in different, non-movement phases of the egress (e.g. pre-movement time). However, this hypothesis should be put under careful scrutiny and analysis of additional experimental and observational data in which social groups are introduced in different ways (e.g. [15]) should help to clarify this notion. Furthermore, my statistical model only considers interactions immediately in front of the bottleneck. It is possible that the desire of social group members to maintain spatial proximity [4] causes substantial self-sorting dynamics in crowds which could impede the crowd flow further upstream or downstream from bottlenecks.

I found a consistent gender-related effect in both of my data sets. Specifically, my findings suggest that there is a shorter time gap between men who follow women than vice versa. There are a number of possible explanations for this finding. For example, the pedestrian crowds I tested may have included many mixed-sex couples which moved closely together with the women moving in front of the men. More prosaically, this finding could be related to average differences in height between genders. As pedestrians exit through the bottleneck, they accelerate. When accelerating, humans shift their upper body forward. This means the position of the head (which I tracked) is shifted forward relative to the rest of the body and the size of this shift may depend on how tall a pedestrian is. If men are on average taller than women in the crowds of participants (which is likely, considering population-wide trends), this could explain the observed effect (men's heads shift forward more relative to women's heads when accelerating). However, with my data I cannot test either of these hypotheses. Considering practical applications, the gender ratio is unlikely to be a sensible parameter that can be controlled to make egress more efficient. I therefore suggest that my gender-related findings are interesting, but difficult to explain and unlikely to be of relevance for applications.

The inconclusive global effects of my treatments are a useful reminder: when conducting experiments with treatments that are designed to alter the behaviour of individuals, it is important to perform multiple replicate experiments with different and independent groups of participants. If only one experimental group is studied, the findings may not generalise and may be caused by alternative factors such as the order in which treatments are tested. While these considerations should be obvious, the expense and time effort required to conduct experiments with large numbers of pedestrians provide a strong incentive to limit the number of groups tested (I only tested 2 groups here).

I suggest that my approach of using statistical modelling to better understand microscopic interactions within crowds provides a useful way forward in this matter. Instead of only analysing one global measure for a crowd (e.g. egress time), I investigate many data points representing instances of potential interactions between individuals. Established statistical theory allows us to test whether these data points can be studied independently or not (e.g. by studying residuals, see [17]). In addition, I have shown that my approach can be used to compare data sets (see also [17]). Finally, I suggest that a particular advantage of my approach is that it allows us to study details of behaviour, but still take other important aspects into account. For example, here I study the effect of social groups and gender whilst accounting for the variability in the data that can be explained by pedestrian positions in front of the bottleneck. My modelling framework is therefore a rigorous approach to quantitatively study pedestrian behaviour, even when it is difficult to collect enough data for investigating effects at the level of the whole crowd.

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